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MACHINE LEARNING FOR THE STORAGE RING OPTIMIZATION

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Abstract

The design and optimization of new lattices for modern synchrotron radiation sources are for the most part art and highly dependent on the researcher's skills. Since both modern existing and designing storage rings is a very complex nonlinear system the researchers spend a lot of effort to solve their problems. In this work, the use of machine learning technics to improve the efficiency of solving nonlinear systems optimization problems is considered.

INTRODUCTION

There are many methods of optimization. All of them can be divided into three groups: determinate, random (stochastic), and combined. It is advisable to use algorithms from each group to solve their group of problems. Different task solving optimization efficiency using different algorithms is presented in Fig. 1.

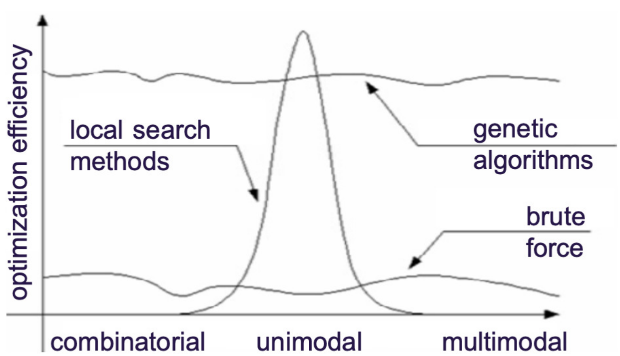

Figure 1: Different task solving optimization efficiency.

Most accelerators and synchrotron radiation sources optimization problems can be attributed to islands of combinatorial problems with many different quality solutions inside an island and between them. An exhaustive search of all solutions or an only subset of solutions is the main feature of combinatorial algorithms. To find the best solution directed, random, and combined an exhaustive search of all possible problem variables is used. Therefore, the search for proper solutions often becomes art. Because very often if you want to optimize nonlinear problem with many variable parameters and restrictions you will face serious difficulties (most rapid and effective optimization methods can't be used, there are many local minima solutions, solving time is directly related to the number of variable parameters, etc.).

So, as you can see in Fig. 1 one of the effective ways to solve multimodal and combinatorial problems within a reasonable time is the use of genetic algorithms. Genetic algorithms are heuristic search algorithms used to solve optimization problems by random selection, combining, and modification of desired parameters using a process like biological evolution. Evolution, as in nature, is an iterative process. The new population from each iteration is referred to as a "generation." The process generally starts with a population that is randomly generated and the fitness of the individuals is evaluated. Individuals with greater/smaller fitness are randomly selected, and their genomes are modified to form the next generation. The average fitness of each generation, therefore, increases/decreases with each iteration of the algorithm. Commonly, the algorithm terminates when either a maximum number of generations has been reached, or a satisfactory fitness level has been achieved for the population.

A genetic algorithm can be used to solve both constrained and unconstrained optimization problems. It likes any other optimization algorithms have their advantages and disadvantages. Their most important advantages may be said to be:

- Any information about the fitness function behavior is not required.
- Discontinuities of the fitness function don't have a significant effect on optimization.
- Methods are relatively stable to fall into local minima.

Their most important disadvantages may be said to be:

- Methods are inefficient for optimizing fitness functions that have a long calculation time.
- A large number of parameters often turns «work with genetic algorithm» to «play with genetic algorithms».
- In the case of simple fitness functions, genetic algorithms are slower than specialized optimization algorithms.

Nowadays, genetic algorithms are powerful computing tools to solve different multidimensional optimization problems. So, the use of genetic algorithms for accelerator and light source optimization allows simplifying and speeds up the search of proper solutions. That's why they have become popular in the accelerator physicist community. The common block diagram for the optimization process using genetic algorithms is shown in Fig. 2.

The long computation time of the fitness function, constraints, and discontinuities are the main features of optimization problems of modern synchrotron radiation sources. When solving this class of problems, any optimization algorithms begin to lose their effectiveness, the time to find satisfactory solutions increases dramatically, and the task of becoming practically unsolvable. To overcome these difficulties, it is necessary to simplify the original problem, divide it into subproblems, reduce the number of variables and the scope of their definition, etc. As a result, the optimization problem becomes solvable but the search time for satisfactory solutions is mainly not reduced.

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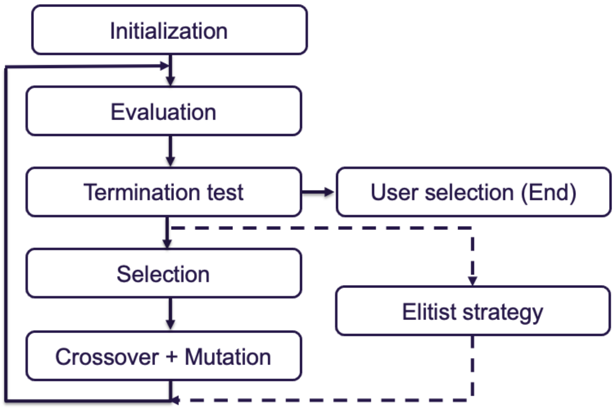

Figure 2: Diagram of the optimization process using genetic algorithms.

So, the main goal of this work is the enhancement of a genetic algorithm to increase the speed and accuracy of searching for solutions to the optimization problem for nonlinear, multidimensional, non-differentiable, multimodal functions with discontinuities in the domain of definition.

DESCRIPTION OF THE PROPOSED METHOD

A specific feature of all genetic algorithms is a lot of fitness function computations at each iteration and a lot of iterations as well. However, to create a new generation of solutions at each iteration, only the solutions obtained at the previous iteration are used. All other previously obtained solutions are no longer used. So, there is a desire to use a large data pool obtained at all previous iterations to speed up the process of solving the optimization problem. One of the best ways to do this is to use machine learning technics and intervene in the evolution process.

Here an intervention method is introduced which is schematically illustrated in Fig. 3. It includes the classification of the search space (unsupervised learning), prediction of the fitness function values (supervised learning), and selection of only potentially best solutions.

In the proposed method the differential evolution algorithm is used [1] as the main global optimization algorithm. Differential evolution uses some of the ideas of genetic algorithms but it does not require working with variables in binary code. This algorithm is simple to implement and can be easily modified anywhere. Also, the differential evolution algorithm was already successfully used to solve the optimization problem in the field of accelerator physics. See [2] for example.

Starting with randomly distributed individuals, the initial population is allowed to produce descendants via the traditional genetic algorithm. After candidates are evaluated at each iteration, all data is accumulated to intervene in the evolution process using machine learning. Next, new candidates of the next generation are created using the tools of differential evolution algorithm. But unlike the conventional approach several crossover and mutation schemes are used. So, n·m·k candidates are created, where n is the population size, m is the number of used crossover and mutation schemes and k is an adjusted integer value.

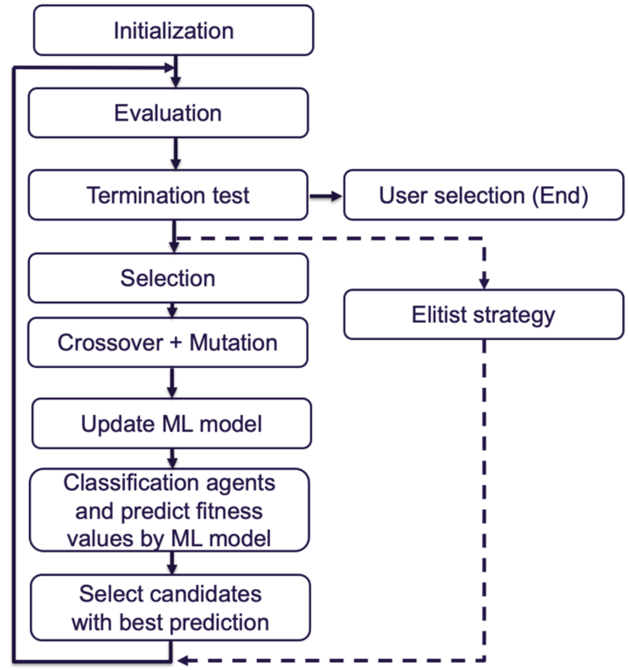

Figure 3: Diagram of the optimization process using genetic algorithms enhanced by machine learning.

On each iteration, the model representation of the fitness function is updated. This model is used to predict fitness function values for n·m·k candidates obtained in the previous step. The value predictions are performed in two steps. In the first step, all candidates are classified into two classes: good and bad. In the second step only for good candidates, the fitness function values are predicted. Next n candidates with the best fitness function values are selected and evaluated. The obtained results are accumulated in the data pool to update the machine learning model of the fitness function.

In the first step SVM [3] and k-NN [4] supervised learning models are used to classify candidates for good and bad. The final decision about the candidate class is made on the results of the two forecasts. In the second step to predict fitness function values for only good candidates the regression model based on the k-NN algorithm is used. Using this approach improves the quality of the final forecast of the fitness function values.

TEST RESULTS

Two different optimization problems are used as an example to demonstrate the application of this method. In the first example, the Rastrigin function is used [5]. This function is very interesting as a performance test problem for optimization algorithms. It is a typical example of a non-linear highly multimodal function, but locations of the minima are regularly distributed and a global minimum is known. Nevertheless, finding the global minimum of this function is a fairly difficult problem.

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A comparison of the evolution of average and minimum fitness for both cases with and without machine learning is shown in Fig. 4. In this test number of variables was 10 and the population size was 1000. So, in these conditions, the conventional differential evolution algorithm could not find the global minimum but found a close enough solution. When the differential evolution algorithm is enhanced by machine learning the situation is improving significantly. Although the global minimum is still not found, the found solution has become much better and found much faster.

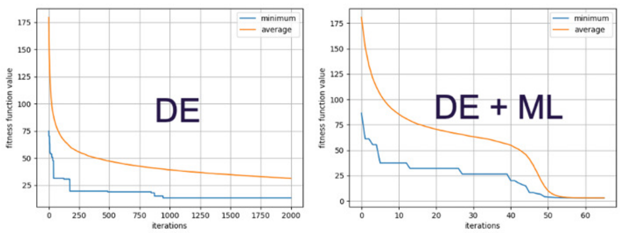

Figure 4: Comparison of the evolution of average (orange) and minimum (blue) fitness (Rastrigin function) without (left) and with (right) machine learning.

In the second example minimization of an electron beam emittance of Kurchatov synchrotron radiation source is used [6]. In this problem, the global minimum is not known and its knowledge is not advisable. Because due to physical and technical restrictions lattice with minimum emittance is not workable. So, in this test number of variables was 6 and the population size was 90 and the results look the same as in the previous test (see Fig. 5). The use of machine learning significantly speeds up the process of solving an optimization problem and allows us to find better solutions.

Note that building machine learning models at each iteration is a time-consuming process and requires significant computational resources especially when a large data pool is used. Therefore, it is not advisable to use machine learning to solve simple problems with fast-calculating fitness functions. In this case, the process of solving an optimization problem will be too long.

Other effective tools for increasing the efficiency of solving optimization problems are a reduction of the dimensionality of the search space for solutions and increasing the efficiency of analysis of the whole search space for solutions.

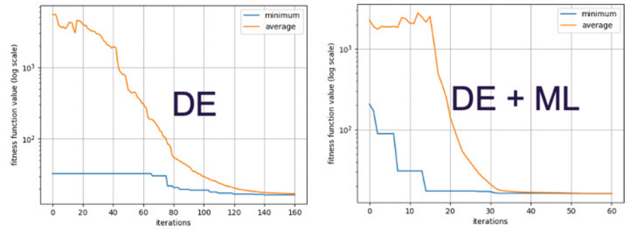

Figure 5: Comparison of the evolution of average (orange) and minimum (blue) fitness (KSRS emittance) without (left) and with (right) machine learning.

SUMMARY AND OUTLOOK

The evolution process of the genetic algorithm significantly speeds up when enhanced by machine learning. Intervention via machine learning not only speeds up evolution but increases the number of elite candidates in the data pool. Greater density of elite candidates allows for the study of the distribution of optimal candidates in the search space.

In this work, the optimizer is driven by the simulated data to realize an offline optimization. Extending it to an online mode would be the next logical step and would be driven by a real storage ring's data.

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